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USE OF ARTIFICIAL NEURAL NETWORKS IN GEOMECHANICAL AND PAVEMENT SYSTEMS

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TABLE OF CONTENTS

FOREWORD

Yacoub M. Najjar, Chairman
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Use of artificial neural networks (ANNs) in geomechanical and pavement systems (i.e., transportation geotechnics) has significantly increased in the past five years. Moreover, their successful application in other fields of decision-making sciences and in computer and electrical engineering is expected to lead to further-increased interest and confidence in their application in all fields of civil engineering. The expert judgements that must routinely be made in transportation geotechnics make it an excellent field for ANN application.

Despite the fact that ANNs have already proved to outperform traditional modeling counterparts in solving various complex engineering problems, their practical use in transportation geotechnics is still limited. The primary obstacles to advantageous implementation of ANNs in transportation geotechnics are lack of understanding and current skepticism. Most of the reported ANN-based studies, even though successful, have not been implemented in practice since practicing engineers are still doubtful of their use. These obstacles can be overcome if the practicing engineers are provided with sources of necessary background information and involved in specifically-oriented ANN workshops and tutorials. This circular and the ANN tutorial session at the TRB 79th Annual Meeting can be considered as a first step toward achieving the goal of overcoming these obstacles.

The main objective of this circular is to provide a source of background information for persons who are unfamiliar with ANNs and their use in transportation geotechnics. The circular is divided into four major parts. In the first part, following the introduction section, several ANN types are briefly discussed and described in approximately the order in which they were introduced in the literature. The second part is the application section, which summarizes the completed applicable work and identifies some tasks for which ANNs are particularly well suited and should continue to be investigated. In the third part of this circular, potential directions for future research are identified and briefly discussed. Part four contains cited references and related books on ANNs. Finally, names and affiliations of all individuals who contributed significantly to this circular, or to the session at the TRB 79th Annual Meeting, or both, are listed alphabetically in the Contributors section.

This circular has undergone peer reviews by representatives of both the TRB Committee on Modeling Techniques in Geomechanics and its Subcommittee on Neural Nets and Other Computational Intelligence–Based Modeling. In all, this circular was sent electronically to 21 researchers in both academia and industry or practice for their critical reviews. Suggestions, additional contributions, and comments received from all reviewers are incorporated in this circular. This circular represents the seventh version of the initial draft document. Based on these reviews, the Modeling Techniques in Geomechanics Committee recommended this information for publication as a circular.

Keywords: Engineering applications, modeling, nonlinear function approximation, neural network, prediction.

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INTRODUCTION

Over the past 2 decades, there has been an increased interest in a new class of computational intelligence systems known as artificial neural networks (ANNs). This type of networks (i.e., ANNs) have been found to be powerful and versatile computational tools for organizing and correlating information in ways that have proved useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle using more-traditional computational methods. ANNs have been successfully used for many tasks including pattern recognition, function approximation, optimization, forecasting, data retrieval, and automatic control. This circular provides an introduction to ANNs and their applications in the design and analysis of geomechanical and pavement systems. As ANNs can be a useful complement to more-traditional numerical and statistical methods, their use merits continued investigation.

ARTIFICIAL NEURAL NETWORKS

The term artificial neural networks encompasses a wide array of computational tools loosely patterned after biological processes. Physically, all ANNs are interconnected assemblages of mathematically simple computational elements. These computational elements contain a very limited amount of local memory and perform rudimentary mathematical operations on data passing through them. The computational power of ANNs comes from parallelism—input data are concurrently operated upon (processed) by multiple computational elements.

Functionally, all ANNs are “vector mappers” (*1*) that accept a feature vector from one data space and produce from it an associated feature vector in another data space. Hopfield (*2*) referred to this as “emergent computation” because the input vectors disappear into the network, becoming unidentifiable once inside, and then emerge as output. Inside the network, data pass between computational elements along weighted connections. Because the data that emerge from the network change as the connection weights change, ANNs can “learn” to produce a desired output by adjusting the signs and magnitudes of their weights. The appropriate adjustments are determined by the computational elements themselves, using learning rules that seek to minimize some type of cost or energy function. Each computational element simply works to improve its own performance. In the process, the performance of the network as a whole is optimized for the task at hand. This parallel distributed processing (*3*) gives ANNs the ability to learn complex mappings without having to specify a priori functions and rules required by conventional computational methods. The user needs only to select the correct type of network and the most appropriate data representation (i.e., feature vectors) for the problem being solved.

There are nearly as many different types of ANNs as there are researchers working in this field. ANNs differ in the arrangement and degree of connectivity of their computational elements, the types of calculations performed within each computational element, the degree of supervision they receive during training, the determinism of the learning process, and the overall learning theory under which they operate (*4*). Despite that, certain types of ANNs appear repeatedly, either because they are broadly applicable to a wide variety of problems or ideally suited for a narrow range of problems. Several of these are briefly discussed herein in roughly the order in which they were introduced.

There are three broad paradigms of learning in neural network technology: supervised, unsupervised (self-organized), and reinforcement. Each category has its own basic training algorithm and a number of variants. In supervised learning (learning with a teacher), adaptation occurs when the system directly compares the network output with a given or desired output. In unsupervised training, the network is trained to identify the irregularities in the data and to form categories based on similarity among the data. Reinforcement learning, one form of supervised training, attempts to learn the input-output vectors by trial and error through maximizing a performance function (named reinforcement signal). The system then becomes able to know whether the output is correct or not, but unable to know the correct output.

Hopfield nets (*5,6*) are fully-connected recurrent networks that store a set of patterns (feature vectors) in such a way that the network, when presented with a new pattern, responds with the stored pattern that most closely resembles the new pattern. The Hopfield net actually implements an energy function in which each stored pattern is a local minimum. Any new pattern introduced to the network will follow the surface of that energy function to the nearest local minimum—the stored pattern that most closely matches it. In such networks, the status of each neuron can be updated independently from that of other neurons in the network; however, all neurons are updated in parallel.

Hopfield nets can be used for

- pattern recognition—selecting one pattern from a set of possible matches,
- pattern completion—providing a complete pattern from incomplete or noisy data,
- classification—identifying a pattern as belonging to a specific group, and
- content-addressable memory—retrieving complete records after given partial information from those records.

If properly designed, Hopfield nets can also be used for optimization. If the optimization problem can be written as a Hopfield energy function, the network can find a near-optimal solution to the problem if given any starting point. Hopfield nets have been used with great success for finding near-optimal solutions to combinatorial optimization problems such as the traveling salesman problem (*7*).

Adaptive resonance theory (ART) networks (*8,9,10*) store sets of patterns and, when presented with a new pattern, match it to previously stored patterns. If the new pattern is not sufficiently similar to any of the existing patterns, an ART network will store it as a new pattern prototype, to which future patterns can be matched. This allows ART networks to evolve over time as they are presented with new data. This process is called unsupervised learning because the network adapts to its information environment without intervention.

ART networks, like Hopfield networks, can be used for pattern recognition, completion, and classification, and as content-addressable memory. They can also be used for knowledge processing (i.e., organizing existing knowledge into groups and identifying new knowledge). In this last capacity, they could be used to detect anomalies in data, because the creation of a new pattern prototype indicates an anomalous feature vector.

Kohonen maps (*11*) (also called self-organized feature maps, SOFM) self-organize to produce consistent outputs for similar inputs. Specifically, Kohonen maps take data (feature vectors) from one data space and project them into a lower-ordered data space (usually a line or plane) in such a way that similar feature vectors project onto points in close proximity to one another. This is called topology preservation. A special case of SOFM is the learning vector quantization (LVQ) networks, which, unlike the basic SOFM, do not preserve topological order. The LVQ networks are very effective in clustering and image data compression.

Kohonen maps can be used for pattern recognition and classification and for data compression (data are mapped into a space with fewer dimensions while as much content as possible is preserved). To illustrate this, researchers could present the colors on a computer screen. If red, green, and blue are combined in varying amounts, millions of colors can be created. Each color is actually a feature vector in 3-dimensional (RGB) space. A Kohonen map can take those 3-dimensional color inputs and project them onto a 2-dimensional plane with a finite number of pixels so that all the yellows cluster together, all the purples cluster together, and so on. The 3-tuple describing each color input has been replaced by the (x, y) location of the pixel that most closely approximates the color.

Back propagation networks are in fact the workhorses of ANNs. They are very powerful and versatile networks that can be "taught" a mapping from one data space to another, using examples of the mapping to be learned. The term back propagation network actually refers to a multi layered, feed-forward neural network (*12*) trained using an error-back propagation algorithm (*13,14,15*). The architecture of a simple back propagation ANN is a collection of nodes distributed over an input layer, hidden layer(s), and an output layer. In the input layer, the input variables of the problems are situated. The output layer contains the output variables, or what is being modeled. In statistical terms, the input layer contains the independent variables and the output layer contains the dependent variable. The nodes between successive layers are connected with links, each of which carryies a weight that describes quantitatively the strength of that connection, thus denoting the strength of one node to affect the other node. As with many ANNs, the connection weights are initially selected at random. Inputs from the mapping examples are propagated forward through each layer of the network to emerge as outputs. The errors between those outputs and the correct answers are then propagated backward through the network and the connection weights are individually adjusted so as to reduce the error. After many examples have been propagated through the network several times, the mapping function is "learned" within some error of tolerance. This is called supervised learning because the network has to be shown the correct answers in order for it to learn. Backpropagation networks excel at data modeling and classification. They have also been successfully used for image compression (they are taught to map the inputs back onto themselves), forecasting, speech identification, and pattern recognition (*16*).

Feedback (sequential) neural networks (FBNN) consist mainly of two sets of input neurons: plan units and current-state units (*17*). These input units feed into a set of hidden units, which in turn feed into a set of output or next-state units. At the initial phase of the training, a pattern of data is presented as an input to the plan units with zero input to the current-state units. Feed-forward process occurs, using initial connection weights and threshold values and producing the first output pattern. This output pattern is then copied back to the current-state units for the next feed-forward sweep. Consequently, the current-state units capture the prior history of activation in the network. This type of network is well suited for modeling the constitutive behavior of geomaterials such as rocks, soils, and concrete (*18–23*). From plasticity theory, it is well known that the current state of stress and strain has important influence on the next state of stress and strain increments. Therefore, it is important to use the FBNN concept of training for simulating stress-strain responses. This feedback approach also ensures that the training phase of the ANN-based constitutive model will be similar to those used in the testing and prediction phases. In any of these phases, the developed ANN-based constitutive model has to incrementally build the entire stress-strain response based on the predictions corresponding to the previous loading steps.

Counterpropagation networks (*24,25*) are hybrid networks that combine supervised and unsupervised learning to create a self-organizing look-up table that can be used for function approximation and classification. As input feature vectors from a training set are presented to the network, unsupervised learning is used to create a topology-preserving (Kohonen) map of the input data while, at the same time, supervised learning is used to associate an appropriate output feature vector with each point on the map. The output at each point is just the average output for all of the feature vectors that map to that point.

Once the network has been trained, each new feature vector presented to the network will trigger a response that is the average for those feature vectors closest to it in the input data space. This is the function of a look-up table. The advantage of this network over conventional look-up tables is that the Kohonen map provides for a statistically optimal coverage of the input space even if the mathematical form of the underlying function is completely unknown. Counterpropagation networks train much faster than backpropagation networks but are not as versatile and are comparatively slower at producing outputs.

Radial basis function (RBF) networks (*26,27,28*) are also hybrids that combine unsupervised and supervised learning to perform function approximation. The concept involves summing a series of overlapping Gaussian functions that can approximate any continuous function. In two dimensions, Gaussian curves are familiar to many as the normal distribution from statistics. In three dimensions, they appear as bumps with radial symmetry. In higher dimensions, they are difficult to visualize, but the concept is equally valid. The use of a Gaussian transfer function rather than sigmoid is what mainly distinguishes RBF from backpropagation networks.

The radial basis function network has a mapping layer in which each neuron represents one Gaussian bump. As with the counterpropagation network, unsupervised learning is used to determine how to best partition the data space given a limited number of neurons. Each neuron is assigned to a cluster of input vectors and affects a Gaussian bump located at the center of the cluster. Once the data space has been appropriately partitioned, supervised learning is used to adjust the heights of the bumps so as to produce the best approximation of the function. When a new input vector is presented to the trained network, it responds with an output that is really just the sum of the outputs from every Gaussian bump in the network, weighted according to the distance from the input vector to the centers of the bumps.

Radial basis function networks also train much faster than backpropagation networks but are not as versatile and are comparatively slower in use because each output requires that dozens (or even hundreds) of Gaussian functions be evaluated.

Generalized regression neural networks (GRNNs) (*29*) are closely related to radial basis function networks. In a GRNN, each neuron in the mapping layer represents a Gaussian bump that coincides exactly with one of the inputs from the training set. Since there is exactly one neuron for each training example, the weights are simply set by hand, using the input and output feature vectors for each example. The training time is therefore zeroed and the weights are initialized to the coordinates of the feature vectors in the training set. Unfortunately, because the training examples do not optimally cover the input space, many of the neurons are wasted, and thus more neurons are needed to achieve the same error level as would occur in a radial basis function network. Therefore, making them even slower than RBF networks at producing an output.

APPLICATIONS IN GEOMECHANICAL AND PAVEMENT SYSTEMS

As might be expected from the wide variety of network types presented in the previous section, there are many different areas in which ANNs have been successfully used in geomechanical and pavement systems. This section will detail applicable work that has already been done and identify some of the tasks for which ANNs are particularly well suited and for which they should continue to be investigated.

The earliest applications of ANNs in pavement systems concentrated on areas such as planning, traffic control and operations, construction and maintenance, and facilities management (*30,31*). The last few years have seen considerable interest in using ANNs for geotechnical engineering applications as well as pavement systems analysis—structural and performance prediction—and design. ANNs have been successfully applied in a full spectrum of geotechnical engineering tasks such as site characterization, foundation engineering, soil liquefaction, and constitutive modeling (*32*). Moreover, a recent workshop proceedings contains a compendium of several papers describing mainly artificial intelligence–based applications and research in pavement and geomechanical systems (*33*).

The majority of ANN-based constitutive models in the literature are for geomaterials, such as subgrade soils and aggregate, rather than for paving materials, such as asphalt and concrete. Penumadu et al. (*34*) developed an ANN-based constitutive model that captured the rate-dependent behavior of clay soils. Tutumluer and Seyhan (*35*) successfully trained a backpropagation ANN to predict the anisotropic stiffness properties of granular materials from standard repeated load triaxial tests (i.e., tests lacking lateral deformation measurements). Zhu and Zaman (*36*) trained a recurrent neural network (a variant of the backpropagation network often used for time-series analysis) to accurately predict the axial and volumetric stress-strain behavior of sand during loading, unloading, and reloading. Using the sequential (feedback) backpropagation training approach, Ellis et al. (*18*) developed an ANN-based constitutive model for sands based on grain-size distribution and stress history. Recognizing the benefits of the feedback approach, Basheer (*20*) and Basheer and Najjar (*21*) used it to simulate the uniaxial stress-strain constitutive behavior of fine-grained soils under both monotonic and cyclic loading. Penumadu and Zhao (*19*) also utilized this approach to model the stress-strain and volumetric behavior of sand and gravel under drained triaxial compression tests. Subsequently, Najjar et al. (*23*) and Najjar and Ali (*22*) have used this feedback approach to characterize the undrained stress-strain response of Nevada sand subjected to both triaxial compression and extension stress paths. Most recently, Ghaboussi (*37*) and Ghaboussi and Sidarta (*38*) have introduced the nested adaptive neural network concept, using it to model both the drained and undrained behavior of sandy soil subjected to triaxial compression–type testing.

Despite exponential advances in computational speed, pavement structural models still expend considerable amounts of computing time. Depending on application, the slowest ANNs can be two or three orders of magnitude faster than elastic layer programs (ELPs) and several more orders of magnitude faster than the most sophisticated finite element programs (FEMs). There are several ways in which function-approximation ANNs can be used to speed the structural analysis task. For example Meier, Alexander, and Freeman (*39*) trained backpropagation networks as surrogates for WESLEA in a computer program for backcalculating pavement layer moduli and realized a fifty fold increase in processing speed. Backpropagation networks were chosen because they are faster than the other function-approximation networks, albeit much harder to train. This is an important consideration when researchers are choosing the appropriate type of neural network to use.

ANNs may never completely replace the versatility of an FEM or ELP, but they can be suitable surrogates as long as the mapping problem is reasonably constrained. It would be unrealistic to expect an ANN to compute stresses, strains, and deflections anywhere in a pavement under any loading conditions. On the other hand, it would be relatively easy to train an ANN to compute, for example, the maximum tensile strain at the bottom of the asphalt-bound layers of a flexible pavement due to a wheel loading. Ceylan, Tutumluer, and Barenberg (*40,41*) illustrated this capability by training ANN models to compute lateral and longitudinal tensile stresses as well as deflections at the bottom of jointed concrete airfield pavements as a function of load location, slab thickness, subgrade support, and the load transfer efficiencies of the joints. The training sets were developed for prescribed dual-wheel and dual-tridem gear loads using the ILLI-SLAB finite element program.

Meier and Rix (*42,43*) trained backpropagation networks to backcalculate asphalt concrete pavement layer moduli from deflection basins obtained using the falling weight deflectometer (FWD). They achieved their goal of increased backcalculation speed by creating a neural network that operates 4,500 times faster than the conventional algorithmic program used at that time. Khazanovich and Roesler (*44*) used a proprietary neural network to perform the same task for data obtained from composite pavements. Ioannides et al. (*45*) used a backpropagation neural network to determine the load transfer efficiency of rigid pavement joints from FWD data. Rolling wheel deflectometers are currently under development, which will make it possible to induce and measure deflection basins at realistic traffic speeds. Neural networks may be the only method fast enough to analyze the enormous volume of generated data in a reasonable amount of time.

Gucunski and his co-workers (*46,47,48*) investigated backpropagation and GRNN networks for simultaneously backcalculating both layer moduli and layer thicknesses from dispersion curves generated by spectral analysis of surface waves (SASW) tests. Meier and Rix (*49*) had previously shown that neural networks could be used to backcalculate the moduli and thicknesses of soil layers from the results of SASW tests. Recently, Kim and Kim (*50*) developed a new ANN-based algorithm for predicting pavement layer moduli using measurements from both FWD and SASW tests. As a forward model, this algorithm employs numerical solutions of multilayered half-space-based Hankel transforms; and it employs an ANN for the inversion process. Though currently more of a research tool than a production tool, SASW is an attractive alternative that may complement or replace FWD and could be significant in the future.

There is great potential for using ANNs to develop predictive distress models. Distress prediction is exactly the type of complex, multivariate problem that has been repeatedly solved using ANNs. Najjar and Basheer (*51*) developed backpropagation ANNs for modeling the durability of aggregate used in concrete pavement construction. A large database acquired from the Kansas Department of Transportation was used to train ANN models, which predicted to a relatively high degree of accuracy the durability factor and percent expansion from five basic physical properties of the aggregate. Basheer and Najjar (*52*) also developed ANN-based distress models to predict longitudinal joint spalling for concrete pavements in Kansas. These models were then successfully employed to address issues related to quality of construction, using parameters pertinent to pavement age, accumulated traffic, and other pavement design elements.

Roberts and Attoh-Okine (*53*) used quadratic function ANNs for pavement roughness prediction. Quadratic function ANNs are generalized, adaptive feed-forward neural networks that combine supervised and self-organized learning. Any of the function-approximation neural networks (backpropagation, radial basis function, counterpropagation, and others) can potentially be used to develop correlations between structural response variables and measures of pavement distress. The key to success is not so much the type of network as the volume and quality of training data.

Banan and Hjelmstad (*54*) illustrated the potential of ANNs for analyzing data from pavement field tests by reexamining the AASHO Road test data using a proprietary ANN, which, like a radial basis function network, subdivides the input space and learns an average response for each subdivision (*55*). By fitting the data locally, the researchers were able to obtain much better data correlations than those obtained using regression, which globally fits the data to a single mathematical function.

Before any predictive distress models can be developed, quantitative measures of pavement distress and performance must be established and methods developed to measure their values over time. This is an area in which neural networks have already shown promise. Kaseko, Lo, and Ritchie successfully used a backpropagation network (*56*) and Lo and Bavarian used a proprietary ANN (*57*) to automatically detect and classify various types of surface cracks in video images of AC pavements. Chou, O'Neill, and Cheng (*58,59*) used backpropagation networks to classify surface cracks that had already been extracted from the video images by other means. Wang (*60*) and Wang et al. (*61*) propose using a neural net computer chip—the Intel Ni1000, which implements a radial basis function network—to automatically detect, classify, and quantify different types of pavement distress at highway speeds.

Another area in which ANNs have already been used is pavement classification. Most state highway agencies maintain permanent traffic recorder stations at strategic locations in order to develop a database of traffic patterns for different road types. This database captures the seasonal variations in the monthly average daily traffic (MADT) at each recorder location. In principle, if you can match a road segment where there is no recorder to one stored in the database, you can forecast its average annual daily traffic (AADT) from a short-term traffic count by applying the seasonal variations stored in the database. In practice, the database is condensed into a handful of road types exhibiting similar traffic patterns and road attributes; this makes it easier to find a match in the database. The task of condensing the database is a classic pattern-classification application at which ANNs excel.

Faghri and Hua (*62*) used an ART network to group road segments according to their MADT patterns. The ART network produced groups with far less data scatter than those developed using conventional methods of cluster analysis and regression analysis. Lingras (*63*) used Kohonen maps for a similar purpose and found them to be a suitable alternative to hierarchical classification methods currently being used for the task. The Kohonen maps were able to classify both complete and incomplete traffic patterns and could evolve over time as traffic patterns changed.

Recently, researchers at the University of Texas at El Paso developed a methodology based on ANN to compute the remaining life of flexible pavements (*64,65*). They used backpropagation neural networks to compute the remaining life of flexible pavements subjected to rutting or fatigue cracking. Their models use the deflection readings from an FWD and the layers' thicknesses. Results of their models have been compared with field data from the Texas Mobile Load Simulator (*66*). An agreement between the models and field data was observed. Currently the ANN models are being integrated into a software tool for integrity evaluation of pavement (*67)*.

DIRECTIONS FOR FUTURE RESEARCH

There is still considerable work to be done in the area of constitutive modeling. Basheer (*20*) proposed techniques for two- and three-dimensional stress-strain modeling of geomaterials, as well as methods for enhancing usability, flexibility, and ability to integrate neural network–based constitutive models in numerical solution techniques such as FEM. ANNs could also be used to model the temperature- and rate-dependent behavior of asphaltic concrete or the fatigue behavior of asphaltic and portland cement concrete (PCC). Models such as these are especially needed because mechanistic design procedures will be based on structural analyses of pavements throughout their design life. This requires that researchers model explicitly, any changes in the behavior of the pavement materials over time due to such things as seasonal variations in temperature and moisture, as well as changes due to fatigue.

Some state highway agencies, such as those in Illinois and North Carolina, have begun monitoring selected in-service pavements for performance. They are keeping records of pavement materials and cross sections, applied traffic loads, and climatic conditions. Similar data have been generated, in even greater volume, from the Long Term Pavement Performance (LTPP) project of the Strategic Highway Research Program (SHRP). The structural response of the pavements to the recorded loads can be calculated using mechanistic analysis programs. By using ANNs, engineers can then correlate the observed pavement performance with the calculated structural response. Because ANNs excel at mapping in higher-order spaces, such models can go beyond the existing univariate relationships (such as those based on asphalt flexural strain or subgrade vertical compressive strain). ANNs could be used to examine several variables at once and the interrelationships between them. ANNs could also be used to develop models for distress phenomena such as thermal cracking, block cracking, and rutting in AC pavements, and faulting and D-cracking in concrete pavements.

Predictive pavement distress models, whether they are developed using ANNs or conventional modeling techniques, will have to be calibrated to local conditions. This is done using shift factors, which adjust the predicted distress development to more realistically reflect field-observed pavement distress and performance. These shift factors not only vary from state to state, but will have to be periodically updated for temporal changes in climate, materials, construction specifications, and traffic. Radial basis function networks would be particularly well suited to this task because they can be incrementally retrained. This is an important point. Some ANNs, such as backpropagation networks, must be completely retrained if additional data become available. Others, such as radial basis function and counterpropagation networks, can evolve over time to accommodate both new data and changed data. The choice of a network type should anticipate future enhancements as well as current needs.

The final area of infrastructural analysis in which ANNs could be used is the modeling of the traffic loads applied to the pavement. Unlike current empirical design procedures based on equivalent axle loads or equivalent aircraft, mechanistic design procedures make it possible to explicitly model the landing gear geometry and wheel loads of each individual vehicle. This requires the user to develop a realistic vehicle mix and project it over the design life of the vehicle. In that capacity, ANNs developed for time-series analysis (such as recurrent neural networks) can play a major role.

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